

Congestion dependencies in the European gas pipeline network during crises

Lubos Buzna

Department of Transportation Networks
University of Zilina
Univerzitna 8215/1
01026 Zilina
Slovakia
Email: Lubos.Buzna@fri.uniza.sk

Rui Carvalho

Statistical Laboratory
University of Cambridge
Centre for Mathematical Sciences
Wilberforce Road
Cambridge CB3 0WB
U.K.

Flavio Bono

European Laboratory for Structural Assessment
IPSC
Joint Research Centre
Via. E. Fermi, 2749 TP 480
Ispra 21027 (VA)
Italy

Marcelo Masera

Energy Security Unit
Institute for Energy and Transport
Joint Research Centre
Westerduinweg 3
NL-1755 LE Petten
The Netherlands

David K. Arrowsmith

School of Mathematical Sciences
Queen Mary University of London
Mile End Road
London E1 4NS
U.K.

Abstract—Conflicts, geo-political crises, terrorist attacks, or natural disasters can turn large parts of energy distribution networks off-line, creating unexpected congestion in the remaining infrastructure. Given the importance of the security of natural gas supply, we need models that enable the management of network congestion, especially during crises. We develop a decentralized model of congestion control to explore the effects of removing supply or transit countries from the network. Recently, in *R. Carvalho et. al. PLoS ONE, Vol. 9, no. 3, 2014*, we evaluated how cooperation between countries helps to mitigate the effect of crises. Here, we extend our previous results by exploring the structure of downstream and upstream congestion dependencies between countries.

I. INTRODUCTION

Natural gas, a fossil fuel that accounts for 24% of energy consumption in OECD-Europe [1], is at the heart of energy security in the European continent. The continent-wide pipeline network that transports gas was designed primarily to connect exporting and importing countries with minimum cost, but not to withstand major conflicts, crises or disruptions. However, looming energy crises have threatened the stability of the system in recent years, with the potential to turn large parts of energy distribution networks off-line and create congestion in the remaining infrastructure. Examples of recent energy crises include disputes between Russia and Ukraine over the price of natural gas 2005-2006, 2007-2008, 2008-2009, the disruption of the oil and gas production industry in the US following Hurricanes Katrina and Rita (2005) or the terrorist attack that affected more than 10 % of Algerian production of natural gas in 2013.

Broadly, there are three approaches to manage congestion [2]. The first, and most obvious, is to expand the network

capacity. The second is to implement congestion pricing to cap the consumption of heavy users that cause network bottlenecks. Finally, the third is to identify groups of countries, users or industries that collaborate to resolve disputes. Here, we expand on our previous results [3] to explore the structure of upstream and downstream dependencies between pairs of countries, when congestion in gas pipeline networks is controlled by a pricing scheme in a way inspired by Internet congestion control.

II. NETWORK MODEL

The data set is organized in four layers, and is fully described in [3]. The first layer is the population density, which we compute from the 2012 Landsat global population data set [4]. The second layer is a graph of the European gas pipeline network, which we extracted from the Platts 2011 geospatial data set. The compiled graph is composed of 2,649 nodes (compressor stations, city gate stations, Liquefied Natural Gas (LNG) terminals, etc.) connected by 3,673 pipeline segments spanning 186,132 km. The third layer is defined by the urban areas in Europe with 100,000 or more inhabitants, and we compiled it from the European Environment Agency and Natural Earth. The fourth data layer is the inter-country matrix T of annual movements of gas via pipelines and of Liquefied Natural Gas via shipping routes [1]. We combine the network data with population density and the borders of urban areas to geo-locate the impact of crises more precisely. Moreover, we make use of population density data to disaggregate country demand given by the T matrix to the level of individual gas nodes.

The capacity of the gas network is assigned to physical point-to-point transport orders by a contract path [5], [6]. The contract path is a route between a pair of source and sink nodes, such that gas flows from source to sink along that path and the transport costs are only incurred on edges along that route. Our model assumes that gas is transported on contract paths, which connect source and sink nodes. To connect sink and source nodes by (contract) paths, we first go through each non-zero entry in the transport matrix T . We edge each sink node in an importing country n to the $\min(10; s_m)$ closest nodes in an exporting country m , if m is a country, or to all LNG terminals, where s_m is the number of gas pipeline nodes in an exporting country m . We estimate the demand associated with each path, and therefore with each sink node, by distributing the volume T_{mn} of gas transported between an exporting country m and an importing country n proportionally to the population density of the importing country [7]. To reach the same demand on all ρ paths in the network, we replace each path by a set of identical paths, each having the minimum demand on the network.

Routing along shortest paths leaves some pipelines unused, but others exceedingly loaded, because the chosen paths minimize source to sink geographical distance, avoiding other slightly longer routes with higher capacity. Here, the problem is solved by re-routing the paths. Therefore, we use a simple iterative algorithm that distributes evenly the capacity c_i of an edge i over the $b_i = \sum_{j=1}^{\rho} B_{ij}$ paths that pass through it, where B is the edge-path incidence matrix (i.e. $B_{ij} = 1$ if edge i belongs to the path j and $B_{ij} = 0$ otherwise). For each source-sink pair, we find the path with minimum effective path length, where the effective edge length is given by $\tilde{l}_i = (\langle h_i \rangle / h_i)^{\alpha} l_i$, given that l_i is the length of edge i and $h_i = c_i / (1 + b_i)$. We observe that $\alpha = 0.03$ maximizes the network throughput, and thus use this value in our simulations.

During periods of crises, the available network resources have to be efficiently used within the remaining infrastructure [9], [10]. Hence, we need a method to handle congestion. The problem of controlling congestion consists in finding a balance between the efficiency and the level of fairness in the access to network resources by individual users [11], [12], [13]. The proportional fairness method, which is inspired by the way the capacity is managed on the Internet [14], is a simple and mathematically powerful way to address the problem of allocating network capacity in flow networks, which is particularly relevant during major crises as it aims at distributing network capacity in a fair way, without compromising throughput. A flow is defined to be proportionally fair if, to increase a flow on a path by a percentage δ , we have to decrease a set of other path flows, such that the sum of the percentage decreases is larger or equal to δ . The proportionally fair path flows f_j are approximated by the system of coupled ODEs:

$$\frac{d}{dt} f_j(t) = 1 - f_j(t) \sum_{i=1}^n B_{ij} \mu_i(t), \quad (1)$$

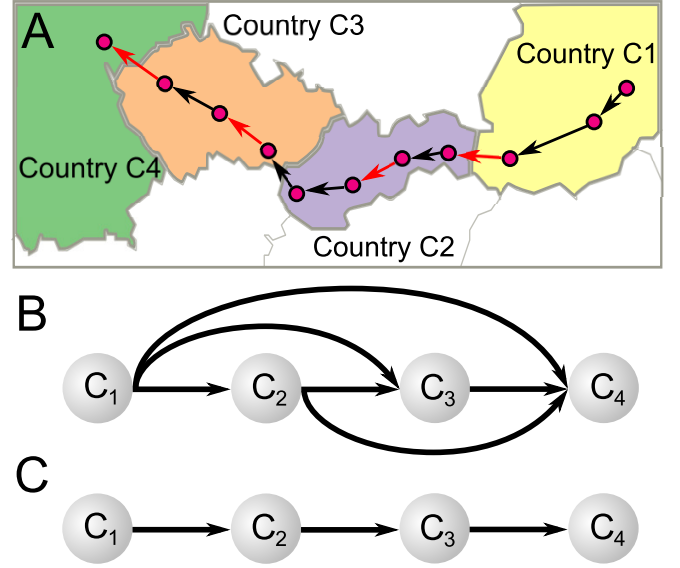


Fig. 1. Diagram illustrating the construction of a congestion digraph. Bottlenecks are identified in red. (A) A path, originating in country C_1 passes through countries C_2, C_3 and terminates in country C_4 , giving the ordered sequence C_1, C_2, C_3, C_4 of countries that contain bottlenecks. If two countries share a bottleneck on a path, as we move along the path from source to sink node, an arc connecting them is added to the digraph. (B) To build a congestion digraph we add arcs between all pairs of countries following the sequence of countries that the path traverses.

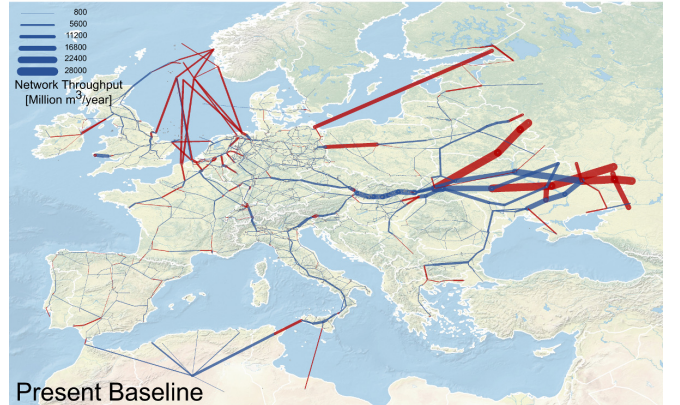


Fig. 2. Map of the proportionally fair flow allocations in the present baseline scenario. Edge thickness is proportional to the flow. Edges in dark red are bottlenecks and edges in blue are not used to their full capacity. The network has 3673 edges, 326 of which are bottlenecks.

where the price on edge i is

$$\mu_i(t) = p_i \left(\sum_{j=1}^{\rho} B_{ij} f_j(t) \right), \quad (2)$$

and the price function is given by

$$p_i(y) = \frac{\max(0, y - c_i + \epsilon)}{\epsilon^2}, \quad (3)$$

where $\epsilon > 0$ is a constant. The algorithm given by Eqs. (1) to (3) solves the proportional fair allocation exactly in the limit

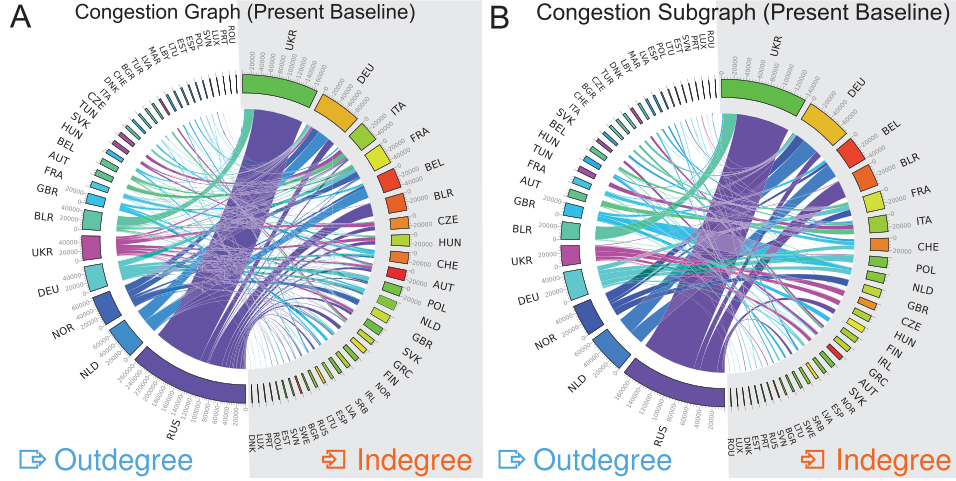


Fig. 3. Congestion digraph and corresponding congestion subgraph, obtained by considering direct dependencies only, for the present baseline scenario (in million cubic meters per year). The circular layout splits country nodes into two parts, corresponding to the in-degree and out-degree.

$\epsilon \rightarrow 0$. A vector of proportional fair flows can be also seen as a reasonable trade-off between two extreme cases: network efficiency (max-flow) and equity (max-min fairness) [15], [16]. The main idea behind the computation of the proportionally fair flows is to use pricing on edges in order to control flow passing through them. If an edge has a free capacity the cost to use it is zero. Above a certain utilization threshold the cost that a path incurs for using an edge steeply increases with the difference between edge capacity and edge utilization (see Eqs. (3) and (2)). Thus, if a path is traversing many congested edges it pays a high cost for contributing to congestion, and thus gets a smaller flow allocation than paths that avoid congestion (see Eqs. (2) and (3)). This approach may also be adjusted to other types of critical infrastructures, such as power grids or road networks.

To study the network resilience we consider two baseline scenarios: the present and future networks. The present baseline scenario corresponds to the network that has been operational since 2011; the future baseline scenario extends the present network by including the planned and under construction pipelines that are available in the Platts database. We analyse two classes of scenarios that consist in hypothetically removing exporting (Russia, Norway, LNG, Libya, the Netherlands and Algeria) or transit countries (Ukraine, the Netherlands, Belarus and Poland) from the baseline scenarios. The scenarios are identified by the baseline (present or future) and the hypothetically removed country. A country scenario consists in removing the national transmission network from the baseline, and, if the country exports gas, replacing with zeros the elements in the row k of the export-import matrix T_{kn} , where k is the scenarios country index. After defining the network and the T_{mn} network for a scenario, we recompute the source-sink pairs, the demand of each pair and we update the routing. Finally, we apply the proportional fairness algorithm to allocate path flows. We give more details on the model in [3].

III. CONGESTION DEPENDENCIES

We say an edge is a bottleneck if it is used to its capacity. The set of bottlenecks that a path j passes through is $\mathcal{H}_j = \{i : B_{ij} = 1 \wedge \sum_{k=1}^{\rho} B_{ik} f_k = c_i\}$. The set \mathcal{H}_j is linearly ordered, that is one can write its elements in a given order $\mathcal{H}_j = \{i_1, \dots, i_{q(j)}\}_{<}$ such that $i_k < i_l$ if bottleneck i_l is located downstream from i_k on path j , where $q(j)$ is the number of bottlenecks in the path j . To increase a path flow f_j assigned to a path j , keeping all other path flows unchanged, we need to increase capacity on all edges in the set \mathcal{H}_j . Hence, bottlenecks separated by large geographical distances are dependent on each other, prompting us to analyse a network of these relationships.

We map country-level dependencies between bottleneck edges by a congestion digraph, with nodes representing individual countries. To do this, we start by defining a source-to-sink path to be $C_m \rightarrow C_n$ if it first passes through at least a bottleneck in country C_m and then downstream through at least another bottleneck in country C_n . We connect country C_m to country C_n by a weighted arc if there is at least one path that is $C_m \rightarrow C_n$. We then weight the arc between countries C_m and C_n by the sum of all path flows of paths that are $C_m \rightarrow C_n$. The upstream congestion dependency between countries C_n and C_m is given by the weight of the arc from country C_m to C_n , and is equivalent to the downstream congestion dependency between country C_m and C_n . Algorithmically, to construct the congestion digraph, we first identify the linearly ordered set \mathcal{H}_j for each path j . We then create a sequence of countries C_1, C_2, \dots, C_l by replacing each subsequence of bottleneck edges located within the same country by one country node (see Figure 1A). Next, we increase the weights $W_{(m)(m+k)}$ of all arcs connecting the pairs of country nodes C_m and C_{m+k} for $m = 1, \dots, l-1$ and $k = 1, \dots, l-m$ by the path flow f_j . Finally, we repeat the procedure for all paths. The congestion graph identifies the

large consumer countries. The largest volume of downstream dependencies appears in source countries, such as Russia, the Netherlands and Norway. Although Norway exports significantly more gas over the transmission pipeline network than the Netherlands, we systematically find larger volume of downstream congestion dependencies for the Netherlands (see Figure 4B). Large gas exporting countries are followed by other important transit countries such as UK, France and Hungary. We not find any major differences between the congestion dependencies for present and future networks.

V. CONCLUSIONS

Congestion dependencies between pairs of countries identify a need for international cooperation when planning to increase network capacity. Indeed, a downstream congestion dependency between countries C_m and C_n in the congestion subgraph indicates that the two countries need to cooperate in their network upgrades, so that an increase of capacity in C_n is matched upstream by an increase of capacity in C_m . We found most of the congestion localized on the periphery of the network, close to the gas source countries. The strongest dependencies are limited to the pairs of neighbouring countries. Due to these prevailing local effects, the localized crises scenarios studied in the paper do not affect the pattern of downstream and upstream dependencies of countries.

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